

# Measuring the Effects of Starting Pitching

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# Outline

- 1 Motivation
- 2 Generalized Linear Mixed Effects Models
- 3 Model Selection
- 4 Predictive Value for Game Outcomes
- 5 Pitching Metrics
- 6 Closing Thoughts

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Github: <https://github.com/przybylee/RunsScoredAnalysis>

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15:35 New York (A) at Toronto ⚡		Main Event	
	RUNLINE	MONEYLINE	OVER/UNDER
New York (A): L Severino	-1.5 -105	-165	O +8.0 -125
Toronto: J Happ	+1.5 -115	+140	U +8.0 +105

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Since runs scored takes values in  $\mathbb{N}_0 = \{0, 1, 2, 3, \dots\}$ , we might consider a model where  $y_{ijkl} \stackrel{\text{iid}}{\sim} \text{poiss}(\lambda_{ijkl})$  is the number of runs scored by team  $i$  against team  $j$  at venue  $k$  during game  $l$ , and

$$\log(\lambda_{ijkl}) = \mu + \omega_i + \delta_j + \nu_k + \chi \mathbf{1}_{ik}. \quad (1)$$

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We will refer to this as the *generalized linear model* (GLM).

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- $\hat{\mu} + \hat{\omega}_{HOU} + \hat{\delta}_{ARZ} + \hat{\nu}_{ARZ} = 1.192$ , meaning the expected runs scored by Houston batting in Arizona is  $\exp(\hat{\mu} + \hat{\omega}_{HOU} + \hat{\delta}_{ARZ} + \hat{\nu}_{ARZ}) \approx 6.85$

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- The Null deviance is 43853 on 4922 degrees of freedom.

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$$\log(\lambda_{ijkl}) = \mu + \chi \mathbf{1}_{il} + b_i + f_j + v_k, \quad (2)$$

$$b_i \stackrel{\text{iid}}{\sim} N(0, \sigma_b^2), f_j \stackrel{\text{iid}}{\sim} N(0, \sigma_f^2), v_k \stackrel{\text{iid}}{\sim} N(0, \sigma_v^2), p_l \stackrel{\text{iid}}{\sim} N(0, \sigma_p^2),$$

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We will refer to this as the *reduced GLMM* (R. GLMM)

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We let  $y_{ijklm} \sim \text{Poisson}(\lambda_{ijklm})$  be the number of runs scored by team  $i$  against team  $j$  at venue  $k$ , against starting pitcher  $l$  during game  $m$ . We have

$$\log(\lambda_{ijklm}) = \mu + \chi \mathbf{1}_{im} + b_i + f_j + v_k + p_l + g_m + e_{im}, \quad (3)$$

$$b_i \stackrel{\text{iid}}{\sim} N(0, \sigma_b^2), f_j \stackrel{\text{iid}}{\sim} N(0, \sigma_f^2), v_k \stackrel{\text{iid}}{\sim} N(0, \sigma_v^2), p_l \stackrel{\text{iid}}{\sim} N(0, \sigma_p^2),$$

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A large estimate for  $\sigma_e^2$ .

# Predictive Value for Game Outcomes

A likelihood ratio test shows that the full GLME model is a much better fit than the reduced version.

To understand the predictive power of these models, we train the model using results from the first 15% of the season and predict on the next 2.5% of the season. This is about 110 games.

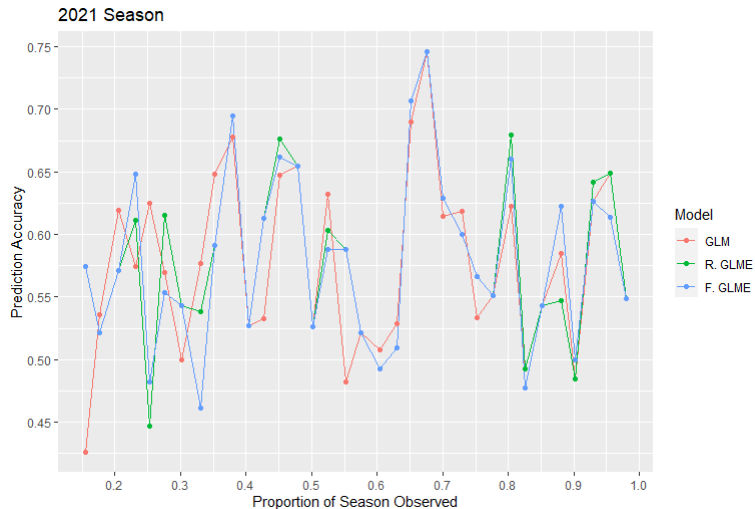
We measure the accuracy of our predictions, then retrain using the first 17.5% of the season and predict on the next 2.5% of the season. We measure and repeat this process for the rest of the year.

# Predictive Value for Game Outcomes

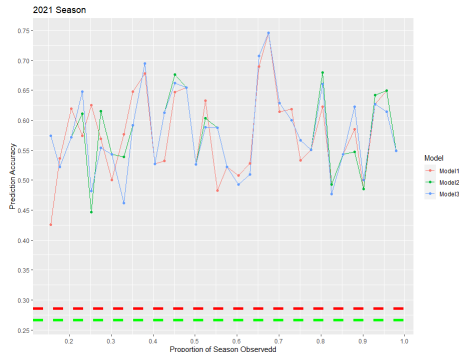




# Model Testing



# Predictive Value for Game Outcomes



Surprisingly the accuracy of the opening and closing money lines was very low. To measure this, we took the proportion of times the losing team had a positive moneyline.

# Pitching Metrics

We can extract the BLUPs for the  $p_j$ 's and assign a value to each pitcher. For each pitcher, we will report  $e^{\hat{p}_j}$  since this is the proportion of runs the pitcher would allow compared to the average pitcher in his environment. We call this score the Starting Pitcher Rating (SRP).

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We consider correlation of SPR with other pitching metrics (ERA, FIP, DRA, WARP).

# Pitching Metrics

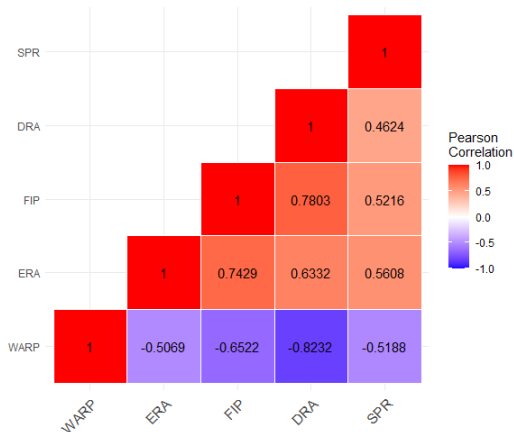


Figure: Correlation Between Metrics in 2021

# Pitching Metrics

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Another value in a pitching metric is its predictive value for future seasons. This has been a major goal since the research by Voros McCracken in the early 2000's that lead us to FIP.

	2015-	2016-	2017-	2018-
#	140	138	151	163
WARP	0.624	0.560	0.549	0.474
DRA	0.562	0.604	0.546	0.518
FIP	0.421	0.426	0.353	0.406
ERA	0.226	0.237	0.228	0.119
SRP	0.158	0.153	0.103	-0.017

Table: Correlation Across Consecutive Seasons



# ERA Leaders

rank	Name	Team	ERA	SPR
1	Aaron Loup	NYM	0.950	0.998
2	Jacob deGrom	NYM	1.080	0.970
3	Dominic Leone	SFO	1.510	0.999
4	Collin McHugh	TAM	1.550	0.989
5	Jesse Chavez	ATL	2.140	0.994
6	Tyler Rogers	SFO	2.220	0.981
7	Louis Head	TAM	2.310	0.999
8	Drew Smith	NYM	2.400	1.008
9	Corbin Burnes	MIL	2.430	0.963
10	Ryan Burr	CWS	2.450	1.001

# FIP Leaders

rank	Name	Team	FIP	SPR
1	Jacob deGrom	NYM	1.230	0.970
2	Corbin Burnes	MIL	1.630	0.963
3	Jesse Chavez	ATL	2.010	0.994
4	Collin McHugh	TAM	2.120	0.989
5	Taylor Rogers	MIN	2.130	0.981
6	Aaron Loup	NYM	2.440	0.998
7	Trevor Rogers	MIA	2.540	0.981
8	Tanner Houck	BOS	2.570	0.996
9	Zack Wheeler	PHI	2.590	0.961
10	Logan Webb	SFO	2.720	0.973

# DRA Leaders

rank	Name	Team	DRA	SPR
1	Jacob deGrom	NYM	2.410	0.970
2	Corbin Burnes	MIL	2.630	0.963
3	Taylor Rogers	MIN	3.000	0.981
4	Michael Kopech	CWS	3.040	0.994
5	Tyler Glasnow	TAM	3.070	0.980
6	Zack Wheeler	PHI	3.150	0.961
7	Brandon Woodruff	MIL	3.180	0.993
8	Gerrit Cole	NYY	3.250	0.989
9	Max Scherzer		3.260	0.953
10	Logan Webb	SFO	3.290	0.973

# 2021 SPR Leaders

rank	Name	Team	SPR	ERA	FIP	WARP	DRA
1	Max Scherzer		0.953	2.460	2.970	4.700	3.260
2	Zack Wheeler	PHI	0.961	2.780	2.590	5.800	3.150
3	Corbin Burnes	MIL	0.963	2.430	1.630	5.500	2.630
4	Shane Bieber	CLE	0.968	3.170	3.020	2.400	3.350
5	Jacob deGrom	NYM	0.970	1.080	1.230	3.300	2.410
6	Logan Webb	SFO	0.973	3.030	2.720	3.600	3.290
7	Lance Lynn	CWS	0.977	2.690	3.310	3.100	3.840
8	Chris Flexen	SEA	0.977	3.610	3.890	0.700	5.220
9	Blake Snell	SDG	0.978	4.200	3.820	2.400	3.930
10	Robbie Ray	TOR	0.979	2.840	3.690	3.900	3.760

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5	Jacob deGrom	NYM	0.970	1.080	1.230	3.300	2.410
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Who? Chris Flexen: 14-7, 2nd most wins in AL

## 2021 SPR Underperformers

rank	Name	Team	SPR	ERA	FIP	WARP	DRA
218	Carlos Carrasco	NYM	1.020	6.040	5.220	0.500	4.770
219	Aaron Nola	PHI	1.020	4.630	3.370	4.300	3.470
220	Riley Smith	ARI	1.022	6.010	4.880	-0.200	5.870
221	Spenser Watkins	BAL	1.022	8.070	6.370	-0.900	6.980
222	David Peterson	NYM	1.023	5.540	4.770	0.600	4.770
223	Johan Oviedo	STL	1.023	4.910	5.270	0.000	5.560
224	Jackson Kowar	KAN	1.026	11.270	6.430	-0.500	7.160
225	Jake Arrieta		1.030	7.390	6.170	0.100	5.460
226	J.A. Happ		1.032	5.790	5.130	-1.800	6.600
227	Dallas Keuchel	CWS	1.036	5.280	5.220	-2.500	6.890

# Closing Thoughts

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- The SPR metric, derived from the model seemed fairly consistent with popular pitching metrics, but demonstrated little predictive value accross seasons.

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- While the model seemed to do fairly well at predicting the outcome games during the 2021 season, the problem is still challenging using only moneyline data.
- The SPR metric, derived from the model seemed fairly consistent with popular pitching metrics, but demonstrated little predictive value accross seasons.
- With the growing impact of releif pitchers, we might consider fitting a model for runs scored in the first 5 innings and derive an SPR from these blups.

# Data Sources and Further Reading

Data:

- <https://www.sportsbookreviewsonline.com/scoresoddsarchives/mlb/mlboddsarchives.htm>
- <https://www.baseballprospectus.com/leaderboards/pitching/>

Jonathan Judge with Baseball Prospectus on DRA:

<https://www.baseballprospectus.com/news/article/26196/prospectus-feature-dra-an-in-depth-discussion/>

Piper Slowinski with Fangraphs on FIP:

<https://library.fangraphs.com/pitching/fip/>

Tom Verducci with Sports Illustrated on Starting Pitchers in 2014:

<https://www.si.com/betting/2020/07/02/gambling-101-major-league-baseball-betting>